## Standards for Proteomics Data Generated by LC-MS-MS

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## Theses:

- Different requirements for data processing, dissemination and storage apply for mass spectrometry applied to the analysis of proteins and proteomes.
- Proteomics is a genomic science and needs to develop "genomics" data analysis/dissemination strategies

# LC-MS/MS as a protein analysis tool

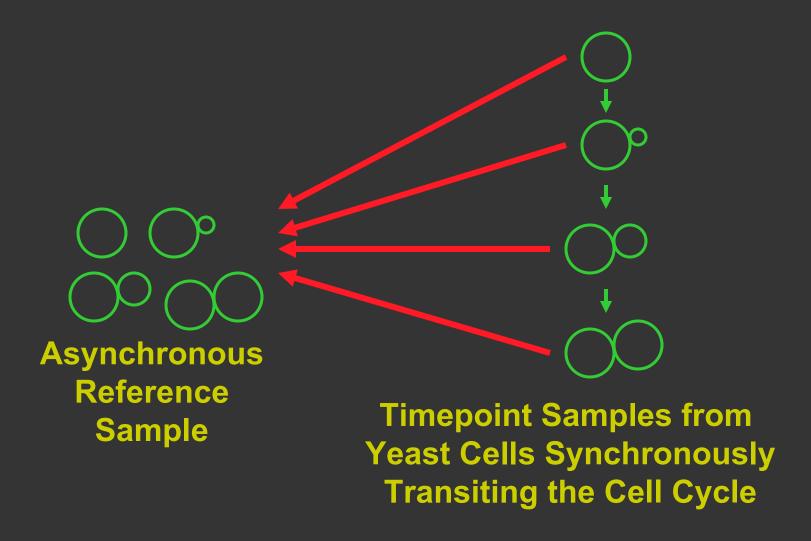
- Relatively low number of proteins analyzed per experiment
- Extensive (biological, manual) validation of data
- Projects centered in single group and focused on specific question
- Data stored in notebook or local computer
- Reports focused on the biological meaning of the data

# LC-MS/MS as a genomic technology

- Many ideally, all proteins in a proteome analyzed repeatedly
- Extensive and consistent biological or manual validation of all data impossible
- Value of information increases if data from multiple experiments/groups can be integrated and collectively mined
- Proteomics is a community effort
- Data are collected and organized in relational databases
- Whole data sets should be made accessible/published

Many – ideally, all – proteins in a proteome analyzed repeatedly, generating large volumes of data

# Synchronous Timepoint Samples Compared to Reference Sample



# Data Summary

	TO	T30	T60	T90	T120
TO	1648	1095	1184	1112	892
<i>T30</i>		1523	1055	1140	921
T60			1448	1051	871
T90				1713	960
T120					1229

- 2735/6562 proteins quantified across all timepoints (42%)
- 696 proteins quantified in every experiment
- 1513 proteins quantified in at least one timepoint
- 34,400 peptides quantified on average per timepoint
- >1 million mass spectra collected

Many – ideally, all – proteins in a proteome analyzed repeatedly, generating large volumes of data

#### **Current status**:

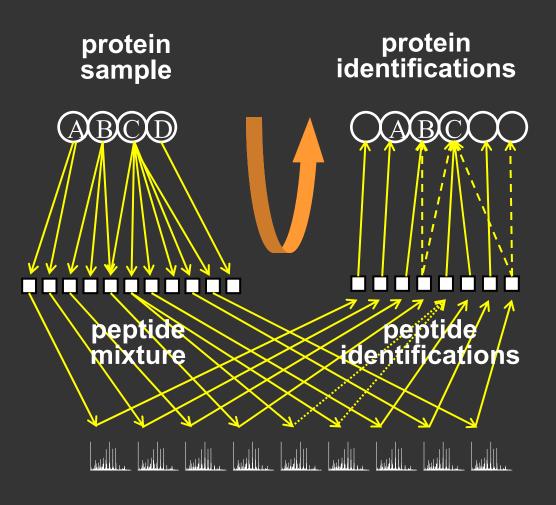
- Large volumes of data are being generated to identify relatively small numbers of proteins
- Information from prior experiments is not used, making the process relatively inefficient

#### **Recommendations**:

- Improved strategies for more efficient data collection and analysis are required
- To develop those, access to data is essential

Extensive biological and/or manual validation of all data impossible

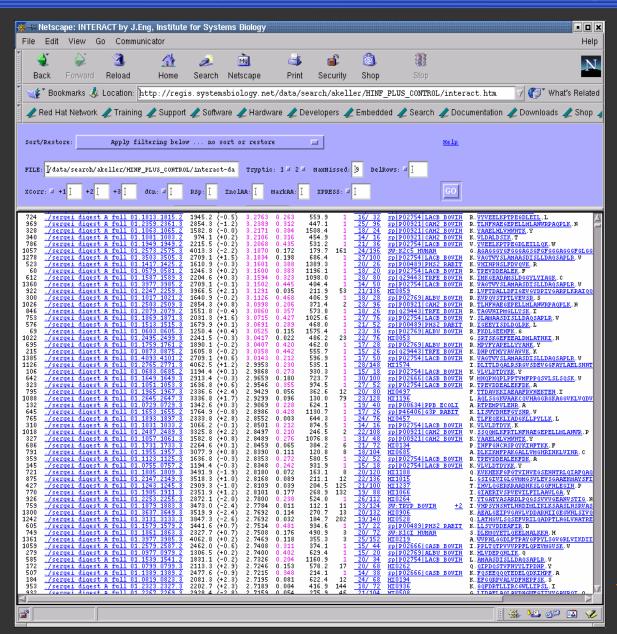
# Protein Identification by MS/MS



MS/MS spectra

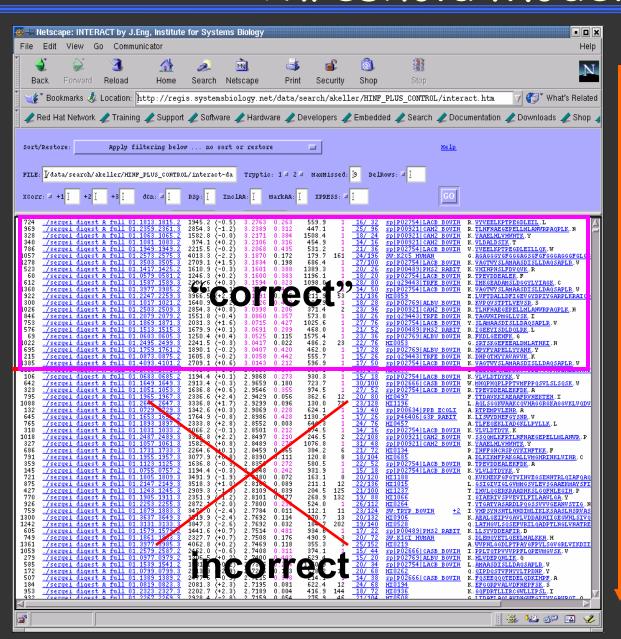


## Output from search algorithm



# sort by search score

### Threshold Model



ort by search score

threshold

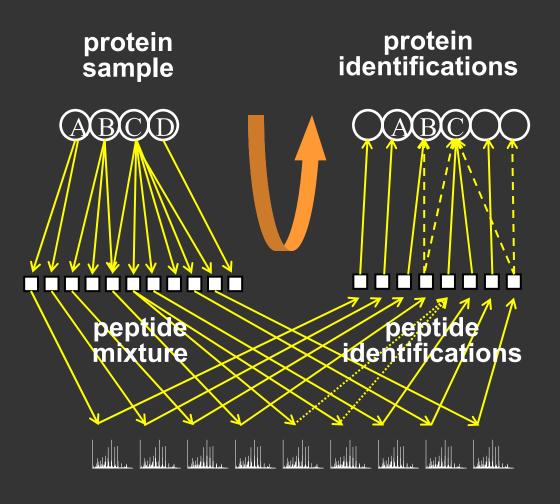
SEQUEST: Xcorr > 2.0 $\Delta C_n > 0.1$ 

MASCOT: Score > 47

# Difficulty Interpreting Protein Identifications based on MS/MS

- Different search score thresholds used to filter data
- Unknown and variable false positive error rates
- No reliable measures of confidence

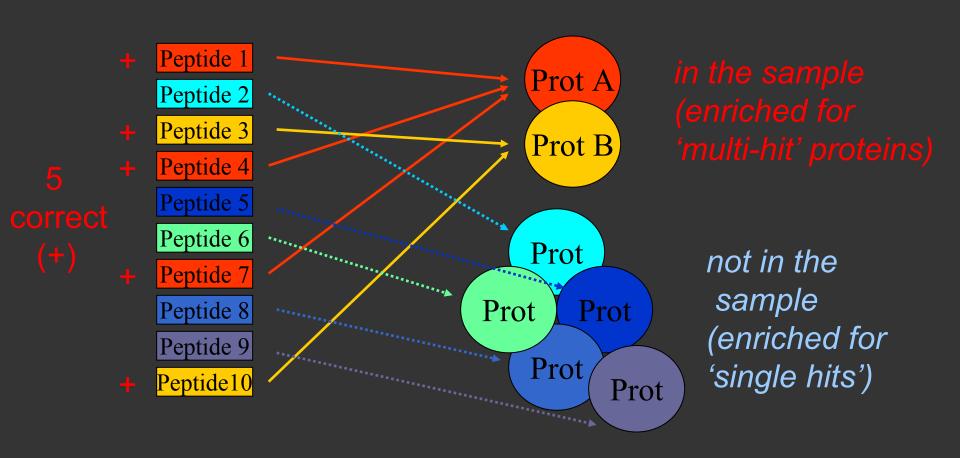
# Protein Identification by MS/MS



MS/MS spectra



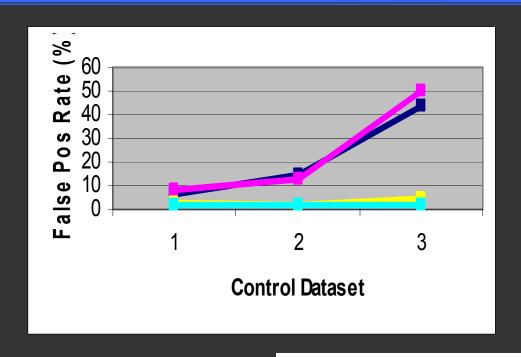
# Amplification of False Positive Error Rate from Peptide to Protein Level



Peptide Level: 50% False Positives

Protein Level: 71% False Positives

# Protein ID False Positive Rate: Control Dataset Examples



#### Data Filters:

Publ. threshold model #1

Publ. threshold model #2

Statistical model (p  $\geq$  0.5)

Statistical model predicted

#### **Control Datasets:**

- 1 18 purified proteins vs. 18+Human (22 runs)
- 2 Halobacterium vs. Halo+Human (4 runs)
- 3 Halobacterium vs. Halo+Human (45 runs)

# False Positive Error Rates among Single-hit Proteins

	Control Dataset				
Data Filter	1	2	3		
Publ. Threshold model #1	11%	37%	67%		
Publ. Threshold model#2	14%	32%	82%		

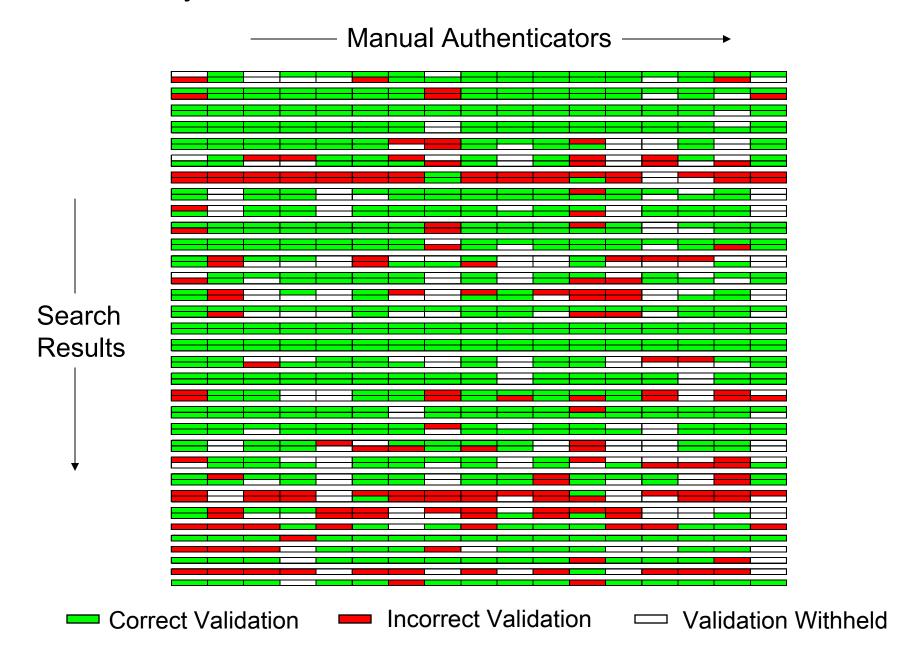
#### **Control Datasets:**

- 1 18 purified proteins vs.18+Human (22 runs)
- 2 Halobacterium vs. Halo+Human(4 runs)
- 3 Halobacterium vs. Halo+Human (45 runs)

# Serum Protein Identifications from Large-scale (~375 run) Experiment

Data Filter	# ids	# non-single hits	# single-hits
Publ. Threshold model#1	2257	359	1898
Publ. Threshold model #2	2742	441	2301
Statistical model, p≥ 0.5  (predicted error rate: 7%)	713	511	202

#### Consistency of Manual Validation of SEQUEST Search Results



# Extensive (biological, manual) validation of all data impossible

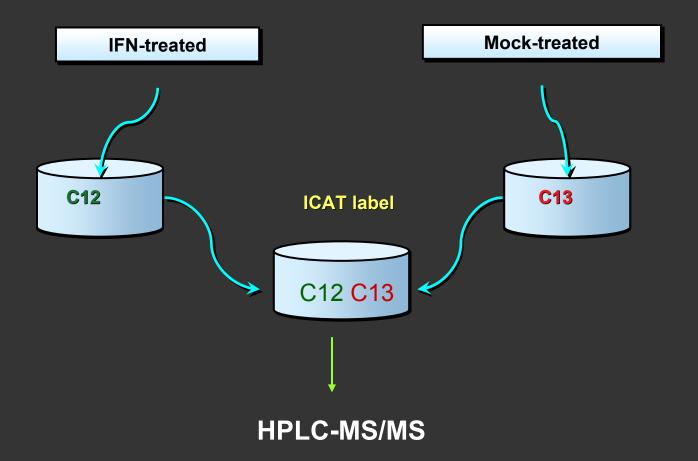
#### **Current status:**

- Peptide and protein identifications are largely made based on threshold model
- Manual validation is often used as "gold standard"

#### Recommendations:

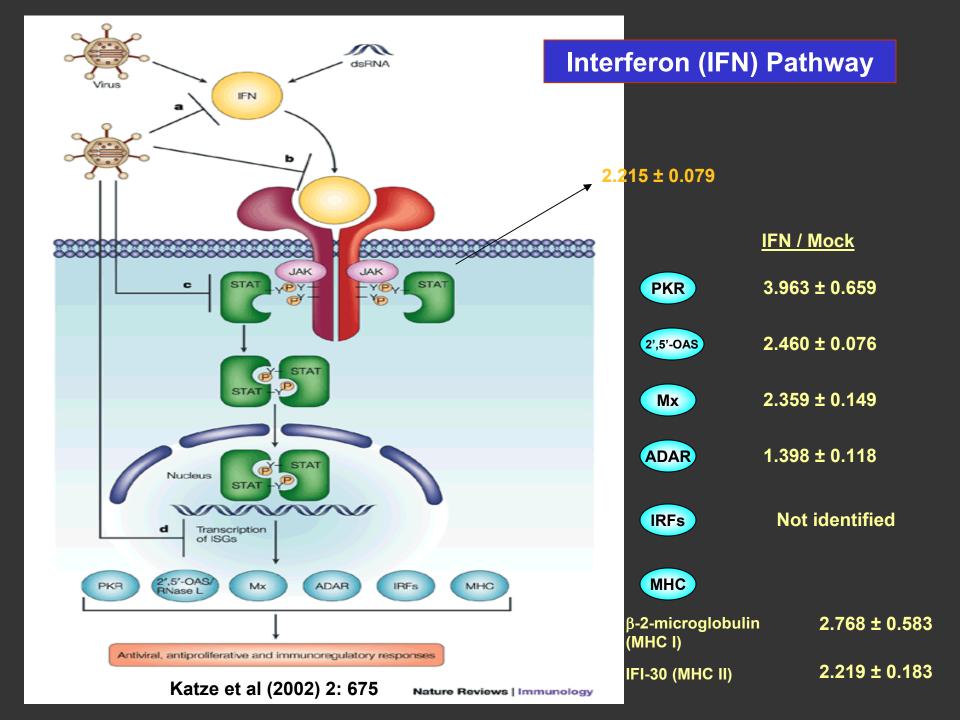
- Develop, validate and use statistical models that calculate accurate false positive and false negative error rates for peptide <u>AND</u> protein identifications
- Discourage manual validation of spectra as "gold standard".
- Tools should be transparent and generally available

- Value of information increases if data from multiple experiments/groups can be integrated and collectively mined
- Proteomics is a community effort
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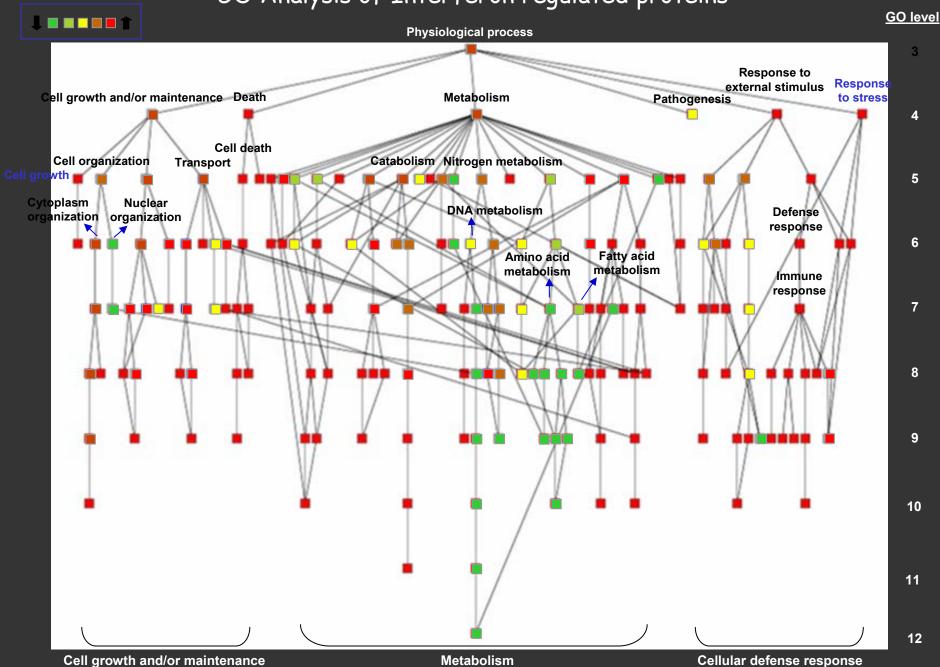


Name			Cellular pathway			Probability	ASAPRatio Mean	ASAPRatio Std.
DNAH11: dynein, axonemal, heavy polypeptide 11  UBE2L6: ubiquitin-conjugating enzyme E2L 6  IFIT1: interferon-induced protein with tetratricopeptide repeats 1  GPR111: G protein-coupled receptor 111			ubiquitination a	moto protein complex ubiquitination and protein degradation unknown and ESIs G-protein coupled receptor and G-protein signaling			9999 9999 9999 21.270	-1 -1 -1 4.741
PASK PAS domain col ADRM1: adhesion res CSA_PPlasePEPTIDY AHCY: S-adenosylhors IFIT4: interferon-indu FLJ32915: hypothetica		S100	P100	Р3	Sum	Uniqu	ie ID	1.024 1.043 1.070 0.936 0.794 4.883
CD7: CD7 anticen (n4: PRK protein kinase.	P ≥ 0.9	523	270	671	1464	111		0.133 0.661 0.751 0.116 2.204
KIAA1276: KIAA1276   NUDT2: nudix (nucleos CABC1: chaperone, Al ACACA: acetyl-Coenzy KNS2: kinesin 2 60/70	P ≥ 0.4	590	330	748	1668	127	2	0.058 0.224 1.659 0.259 0.335
LOC151636: rhysin 2			<del>-</del>	nd intracellular tran	asport?	1	2.975	0.231
M96: likely ortholog of mouse r factor 2	metal response element	t binding transcription	transcription			0.98	2.923	0.390
ETFA: electron-transfer-flavopi	rotein, alpha polypeptid	e (glutaric aciduria II)	electron transfe	er		0.45	2.890	0.484
NMI: N-myc (and STAT) inter	actor		signaling pathv	/ay; transcription		0.57	2.875	0.138
GSA7: ubiquitin activating enzy	· · · · · · · · · · · · · · · · · · ·		ubiquitination a	nd protei		0.98	2.844	0.663
MGC3207: hypothetical protein	n MGC3207					0.61	0.499	0.071
SPK: symplekin  KRT10: keratin 10 (epidermoly plantaris)	rtic hyperkeratosis; kera					0.97	0.496 0.495	0.029 0.055
SARDH: sarcosine dehydrogei	nase	EATEN:		-4-1 /0	4-1-1	0.98	0.484	0.008
TRA1: tumor rejection antigen		<b>54 IFIN-</b>	induced pr	oteins (2	2-TOIQ)	1	0.452	0.165
GPS1: G protein pathway supp						0.98	0.455	0.138
SRRM2: serine/arginine repeti		15 r	reviously i	reported		0.82	0.434	0.224
KIAA0007: KIAA0007 protein			neviously	cported		1	0.426	0.014
FACL4: fatty-acid-Coenzyme A	A ligase, long-chain 4					0.98	0.416	0.081
FXR2: fragile X mental retarda	tion, autosomal homolo	39 r	iovel			0.95	0.391	0.074
TUBA6: tubulin alpha 6						1	0.383	0.165
CPSF4: cleavage and polyade	enylation specific factor	4			/O F C 1 D	0.96	0.378	0.154
MAPRE1: microtubule-associa	ited protein, RP/EB fam	23 IFN-I	repressed	proteins (	(U.5-fold)	0.98	0.339	0.016
OAT: ornithine aminotransfera	se (gyrate atrophy)					0.98	0.331	0.018
PPGB: protective protein for be						1	0.323	0.084
WNT9A: wingless-type MMTV	integration site family, r	memb				0.99	0.316	0.091
FASN: fatty acid synthase				cid metabolism		0.99	0.304	0.100
Ig lambda chain C regions	-1		immune respor			0.98	0.265	0.110
G2AN: alpha glucosidase II alp			carbohydrate n	netabolism		1 0.71	0.198	0.033
Hypothetical protein FLJ21140				unknown			0.043	0.064
KRT6: keratin 6 MIG-6: Gene 33/Mig-6			cytoskeletion and intracellular transport			1 0.99	0.003 0.000	0.008 -1.250
MIG-6: Gene 33/Mig-6 signaling pathway  HIC1: hypermethylated in cancer 1 transcription suppression					0.99	0.000	-1.250 -1.250	
The f. hypermethylated in cand	7C1		u anscription st	hhisaanii		0.94	0.000	-1.∠50

Lots of data -what does it mean?

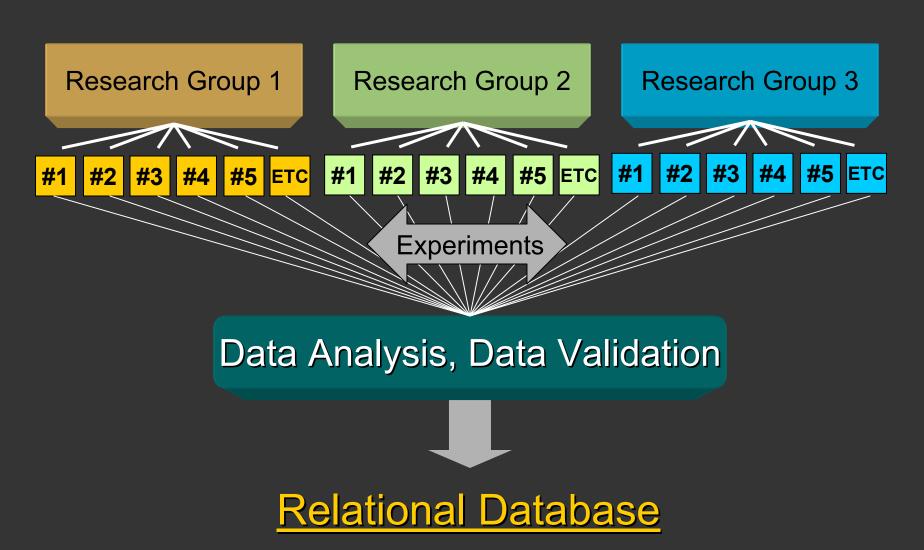


#### GO Analysis of Interferon regulated proteins

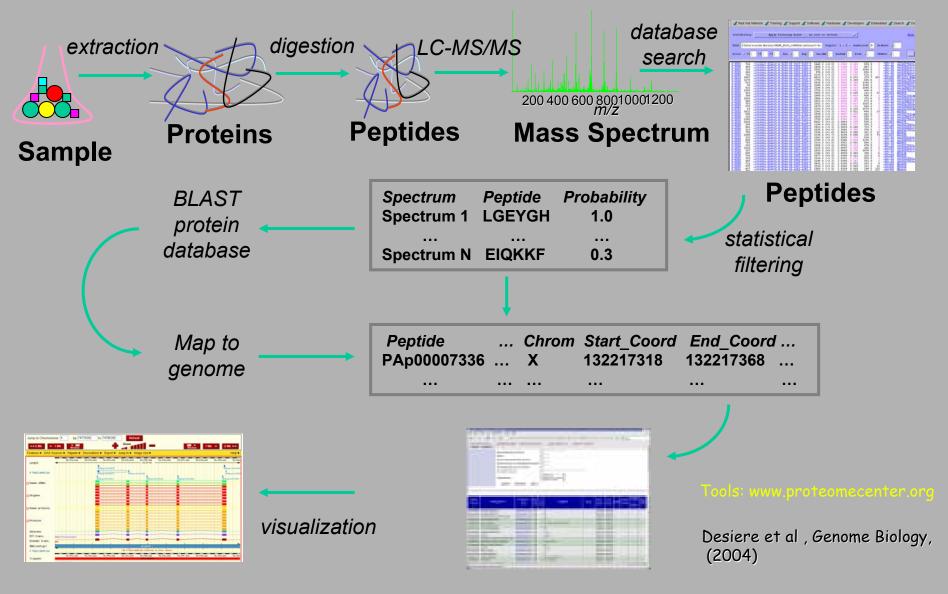


- Single proteomics datasets tend to rediscover the known
- New insights can be made from the comparison of many datasets

# Data collection in proteomics



## From Peptides to Genome Annotation



**Genome Browser** 

**PeptideAtlas Database** 

- Value of information increases if data from multiple experiments/groups can be integrated and collectively mined
- Proteomics is a community effort
- Data are collected and organized in relational databases

#### **Current status**:

- Very little proteomics data publicly accessible
- Publications usually only show conclusions but not data

#### Recommendations:

- Develop and support infrastructure for data sharing and mining
- Make data access condition for publication

# Summary

If proteomics is to truly operate as a discipline of the genomic sciences, data processing, management and dissemination strategies proven in other fields of genomics must be applied. These include:

- Statistical validation of large data sets
- Providing community access to all data (not just selected data points)
- Providing transparent tools for data processing to community